Asymmetry in Subseasonal Surface Air Temperature Forecast Error with Respect to Soil Moisture Initialization

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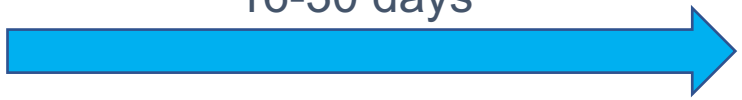
Questions? Contact Randal Koster (randal.d.koster@nasa.gov)

Basic Mechanism: Soil Moisture Impact on T2M Forecasts

Soil moisture is anomalously wet at the start of a forecast

16-30 days



Soil moisture is still (somewhat) anomalously wet at subseasonal lead (soil moisture memory)

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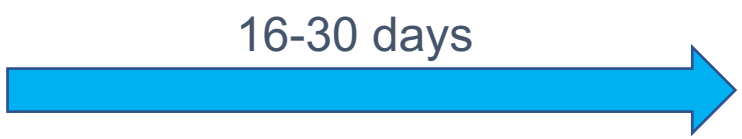


Soil moisture is still (somewhat) anomalously wet at subseasonal lead (soil moisture memory)

⇨ Evapotranspiration is higher at subseasonal lead

Basic Mechanism: Soil Moisture Impact on T2M Forecasts

Soil moisture is anomalously wet at the start of a forecast

16-30 days

Soil moisture is still (somewhat) anomalously wet at subseasonal lead (soil moisture memory)

⇨ Evapotranspiration is higher at subseasonal lead

⇨ T2M is lower at subseasonal lead (evaporative cooling)

Basic Mechanism: Soil Moisture Impact on T2M Forecasts

Soil moisture is anomalously dry at the start of a forecast

16-30 days

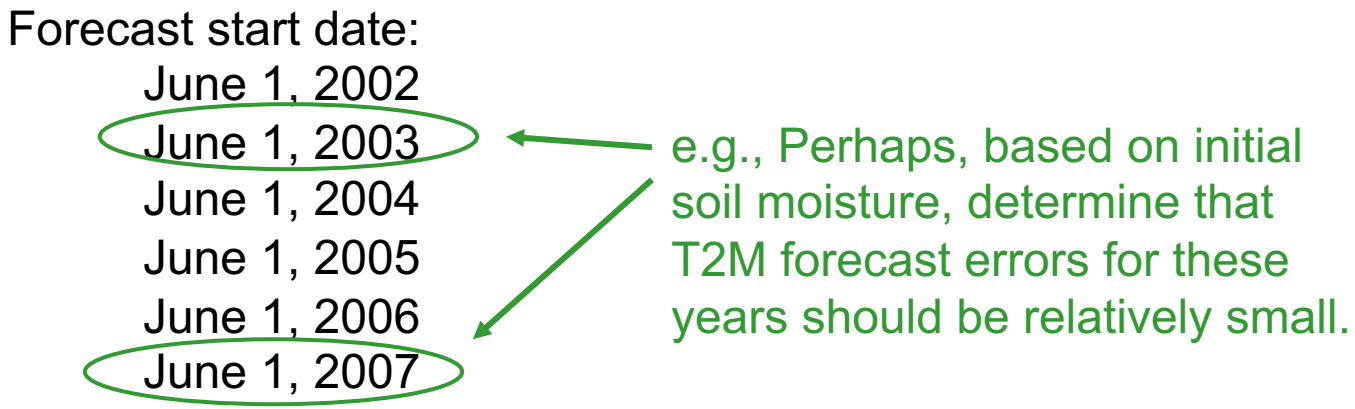
Soil moisture is still (somewhat) anomalously dry at subseasonal lead (soil moisture memory)

⇨ Evapotranspiration is lower at subseasonal lead

⇨ T2M is higher at subseasonal lead (evaporative cooling)

And, of course, the reverse!

Basic question examined here: Can we use the initial state of the soil moisture to identify when a temperature forecast is more trustworthy?



Such information could be of substantial benefit to forecast end-users.

Lead considered: Days 16-30.

Breakdown of forecast T2M error (relative to CPC station observations) :

$$RMSE^2 = bias^2 + ubRMSE^2$$

unbiased root-mean-square error, the random error (associated with chaotic dynamics) in an unbiased forecast

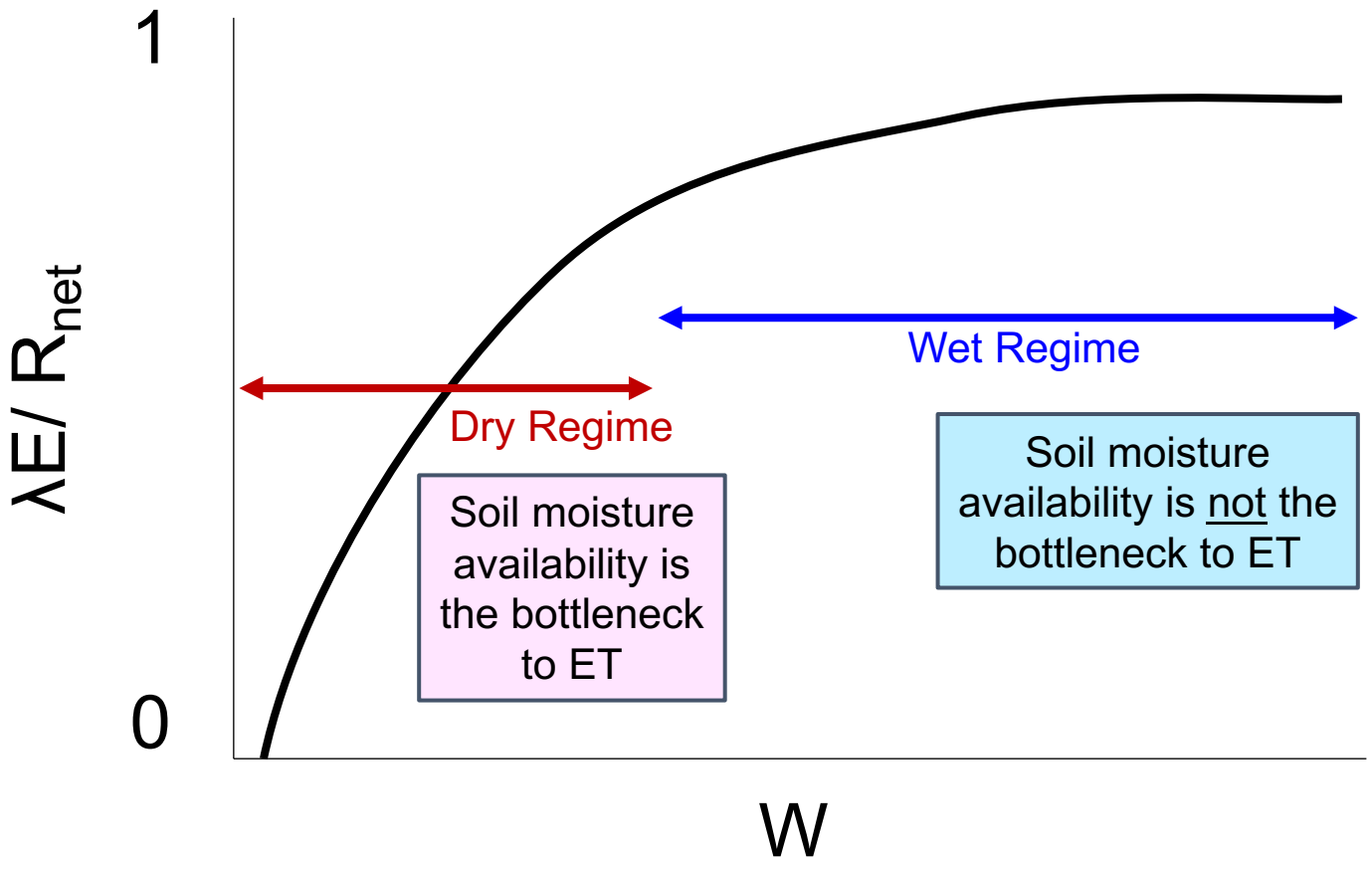
Lead considered: Days 16-30.

Breakdown of forecast T2M error (relative to CPC station observations) :

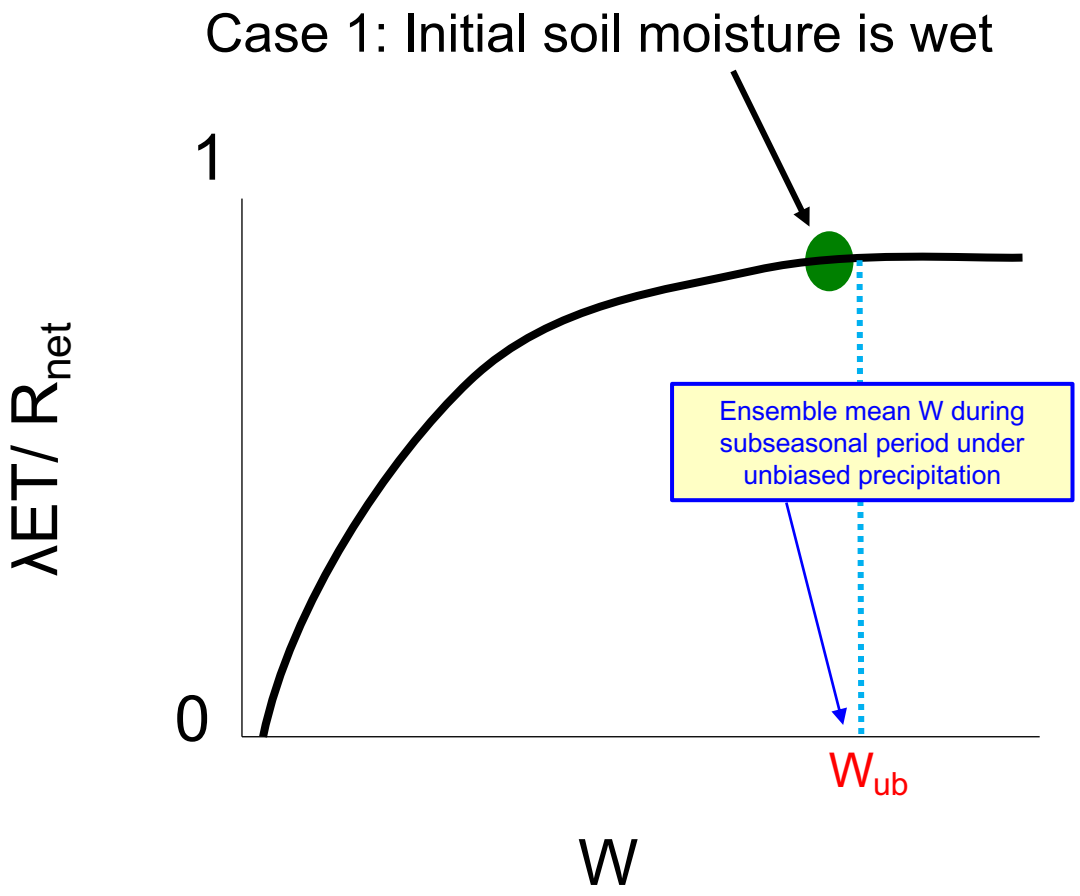
$$RMSE^2 = bias^2 + ubRMSE^2$$

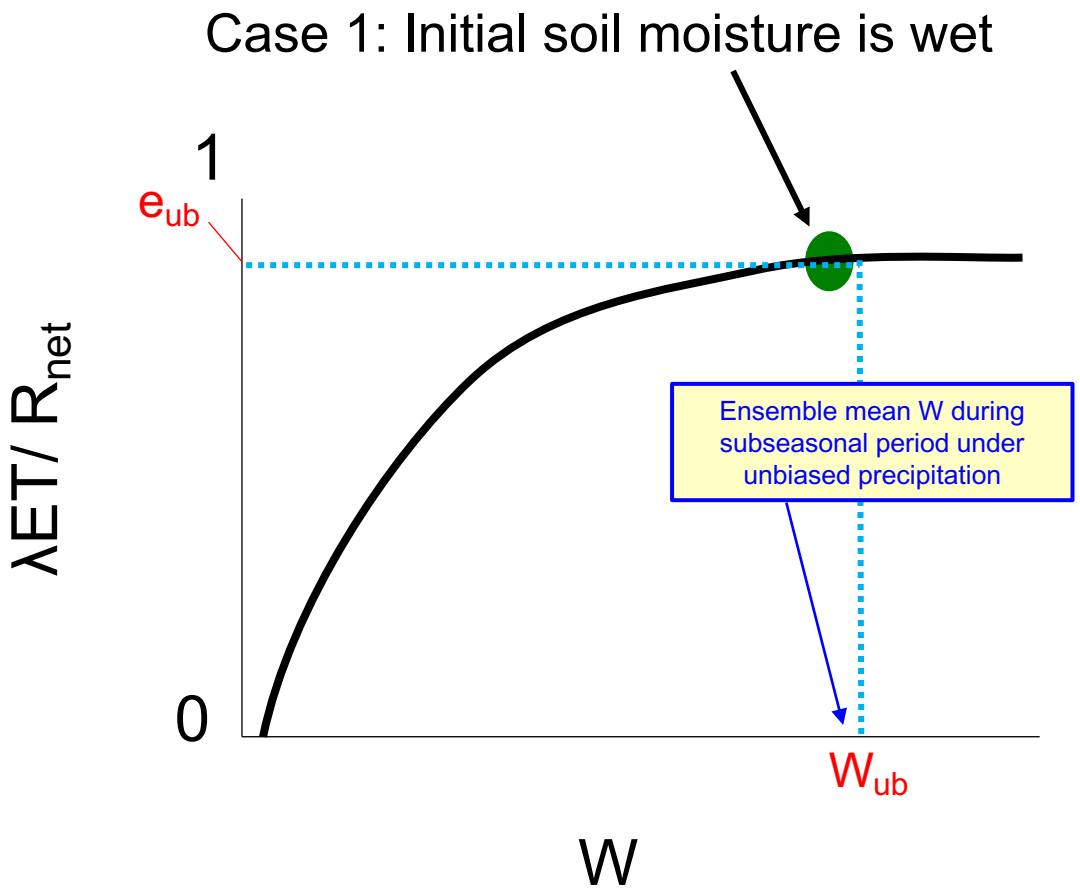
Mechanism 1: A focus on bias

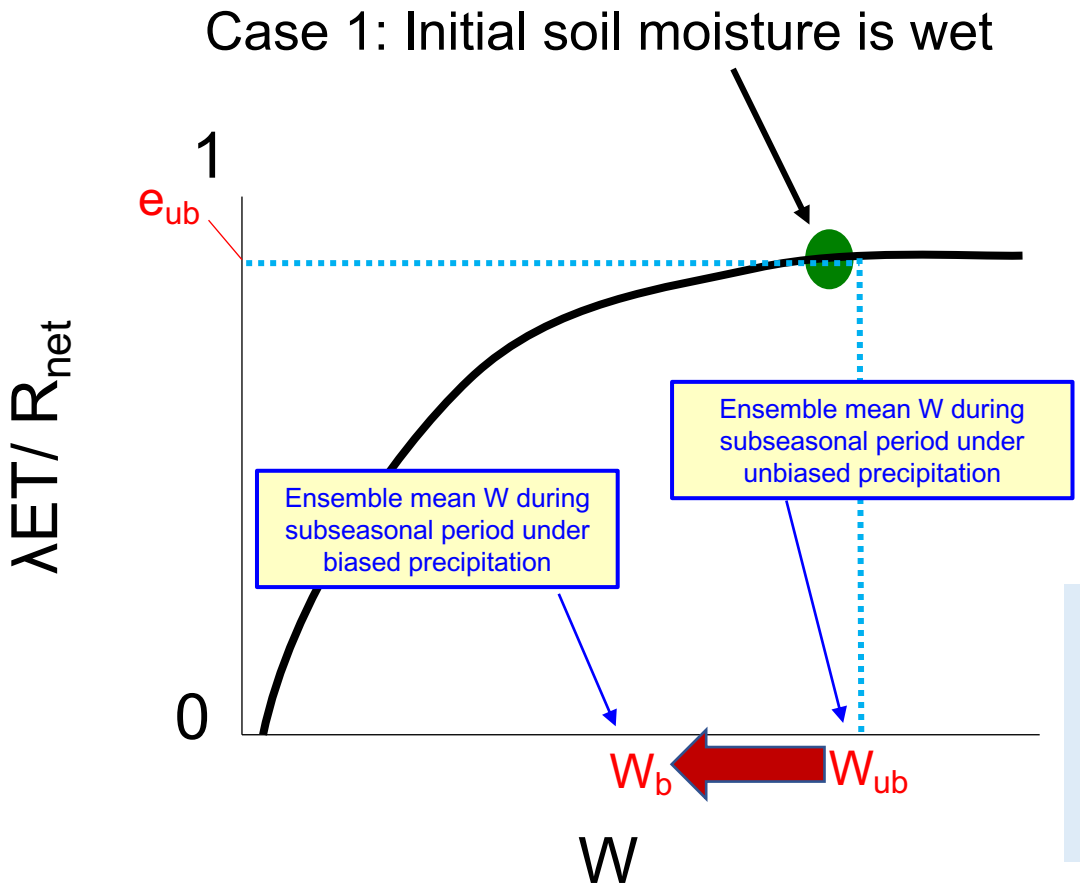
Canonical relationship between soil moisture (W) and evaporation efficiency



Given this relationship, consider the impact of a wet versus dry soil moisture initialization on a forecast.

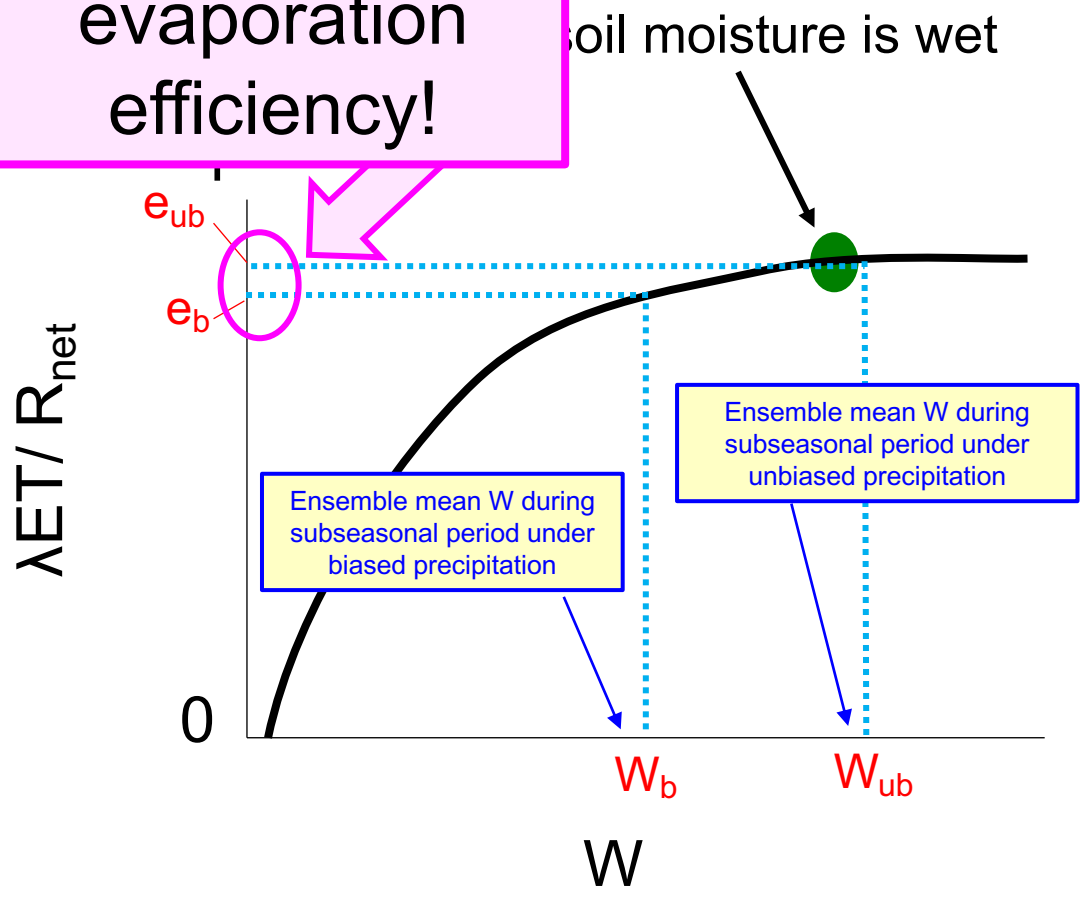

Case 1: Initial soil moisture is wet
1
0
λET/ Rnet
Ensemble mean W during subseasonal period under unbiased precipitation
Wub
W


Case 1: Initial soil moisture is wet
1
e_{ub}
0
$\lambda ET / R_{net}$
Ensemble mean W during subseasonal period under unbiased precipitation
W_{ub}
W



Suppose now that in the forecast model, the precipitation is biased low ⇨ the soil moisture obtained in the forecast would also be biased low.

Small negative bias in evaporation efficiency!



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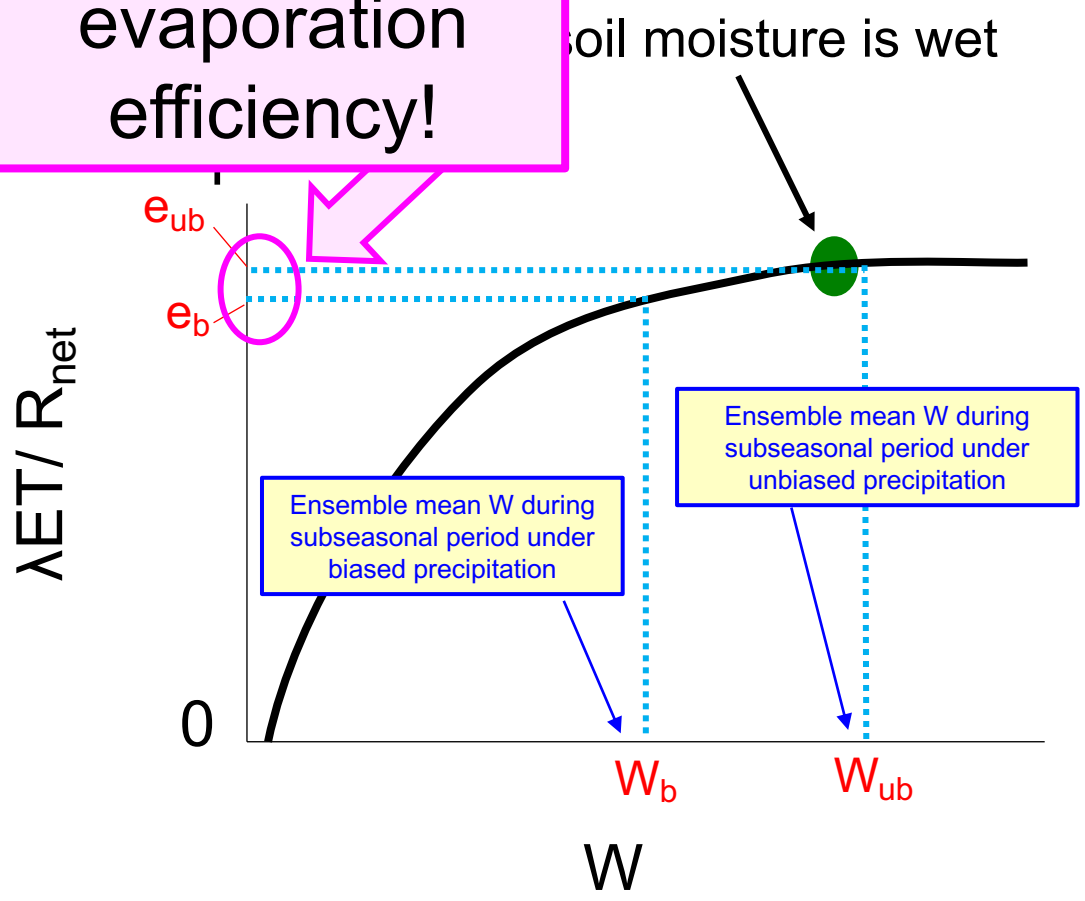

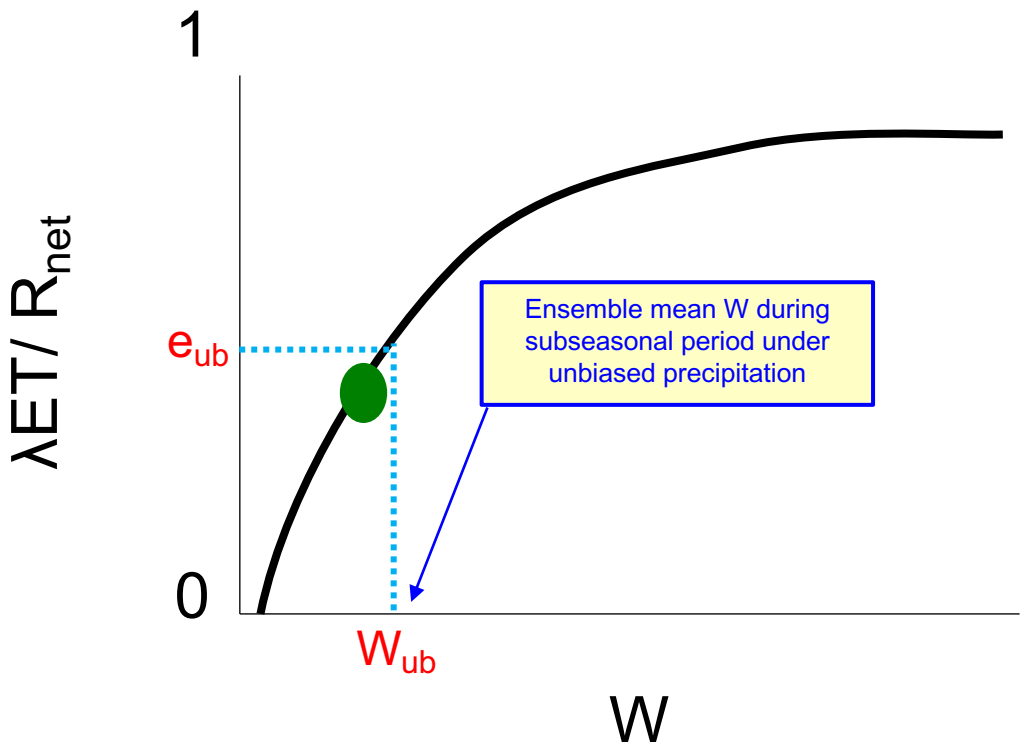

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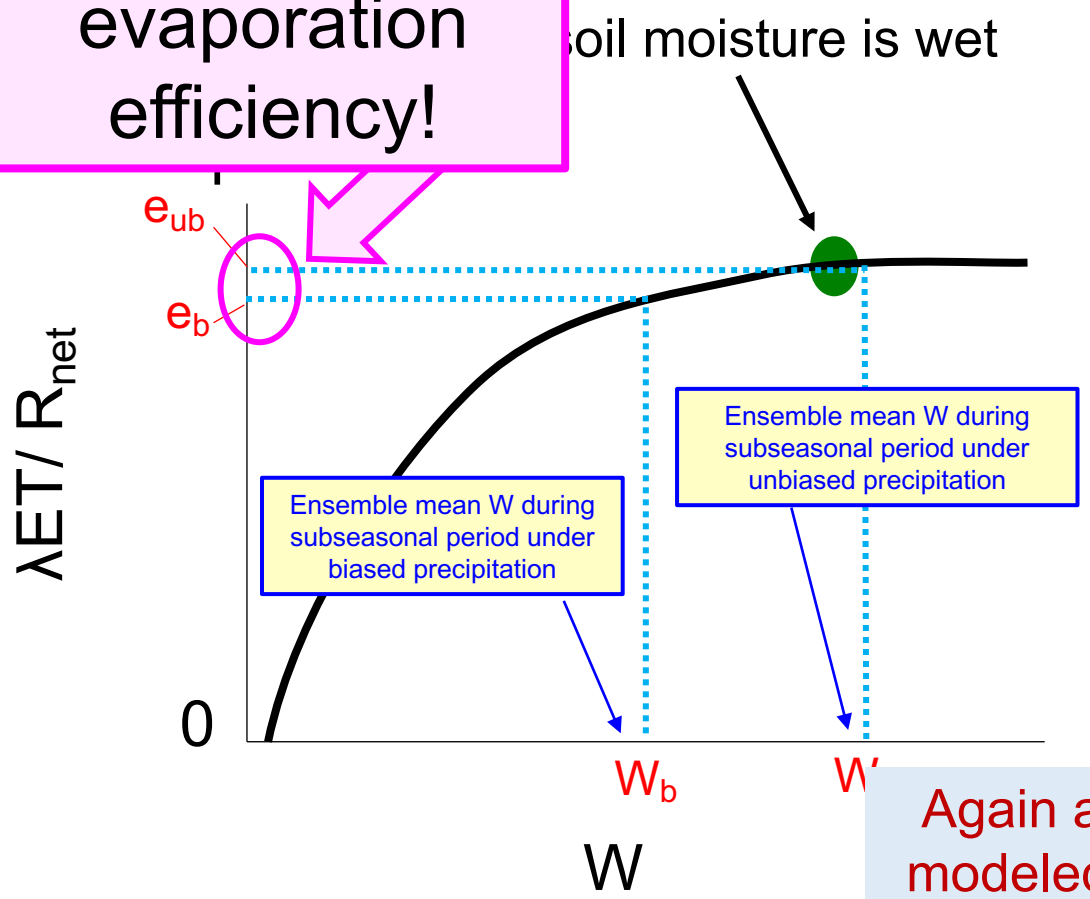
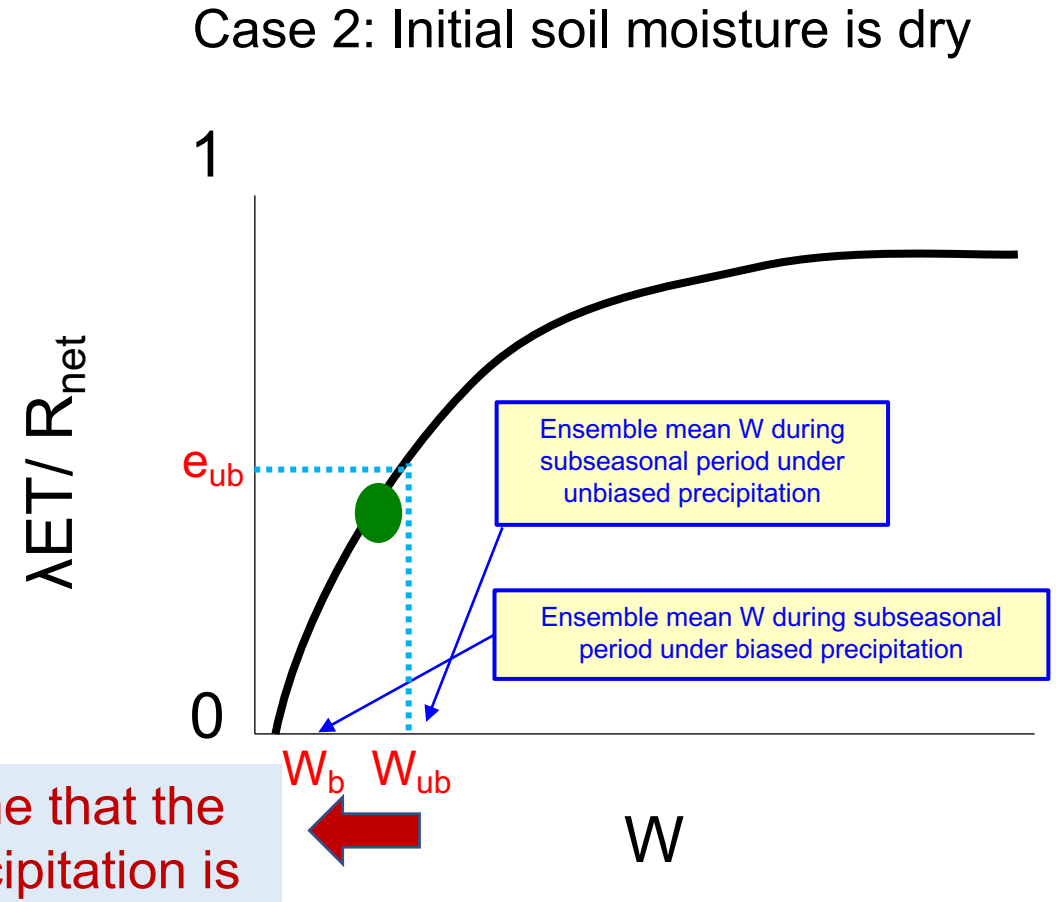
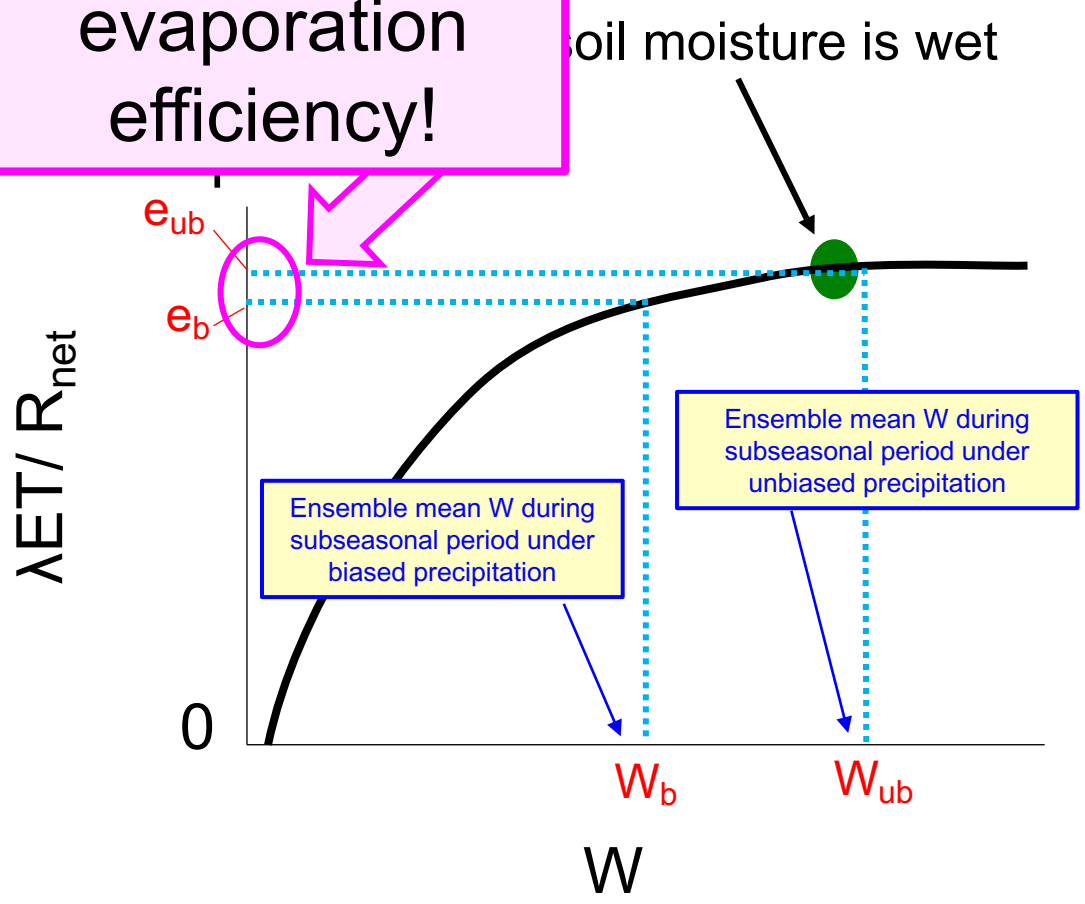
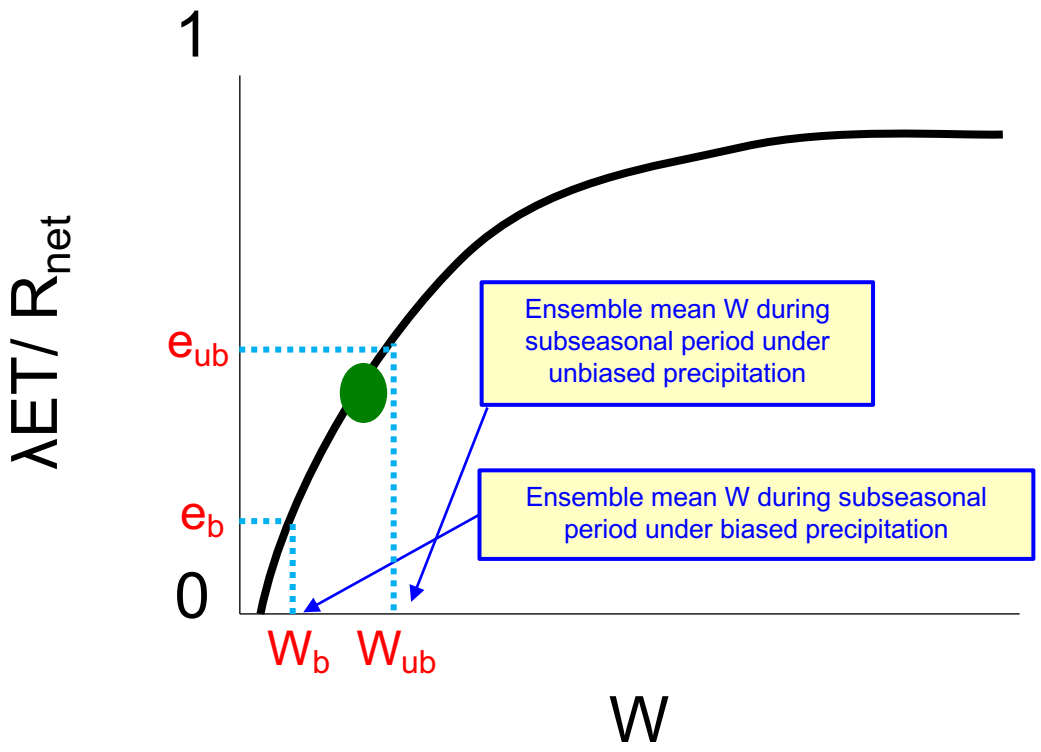




Again assume that the modeled precipitation is biased low.

Small negative bias in evaporation efficiency!





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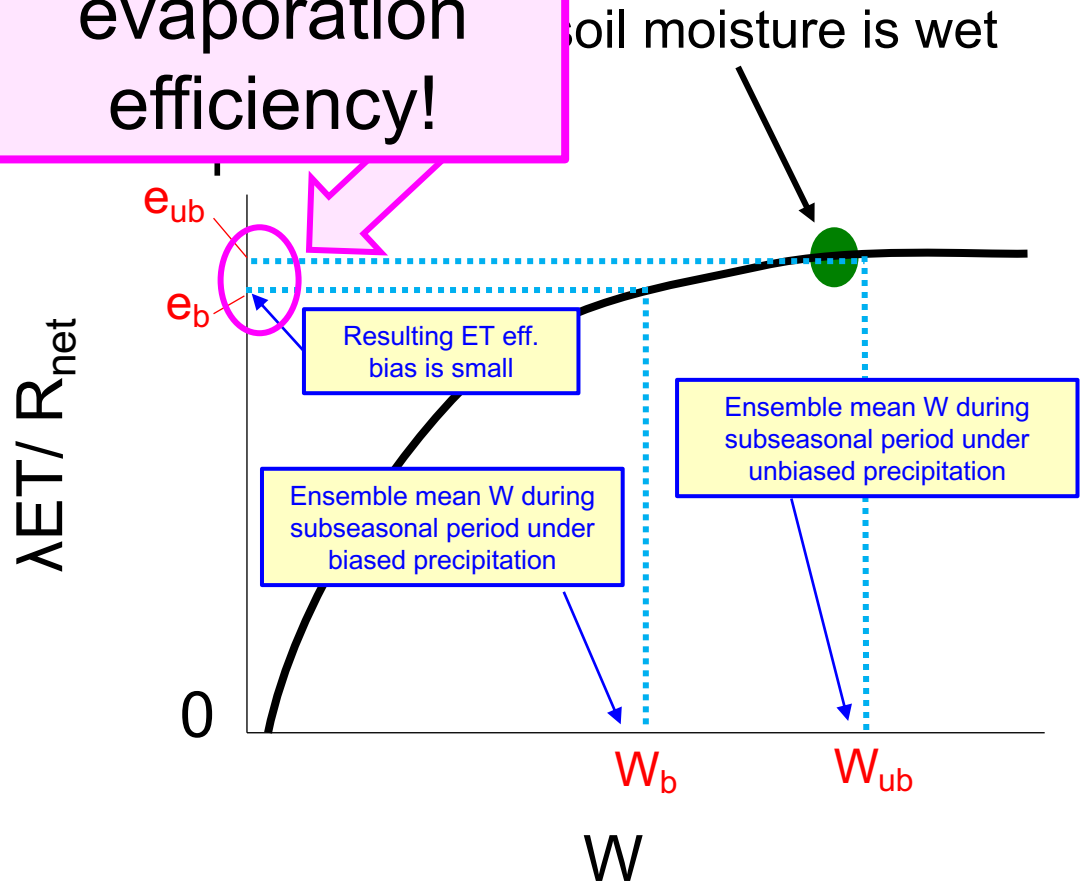

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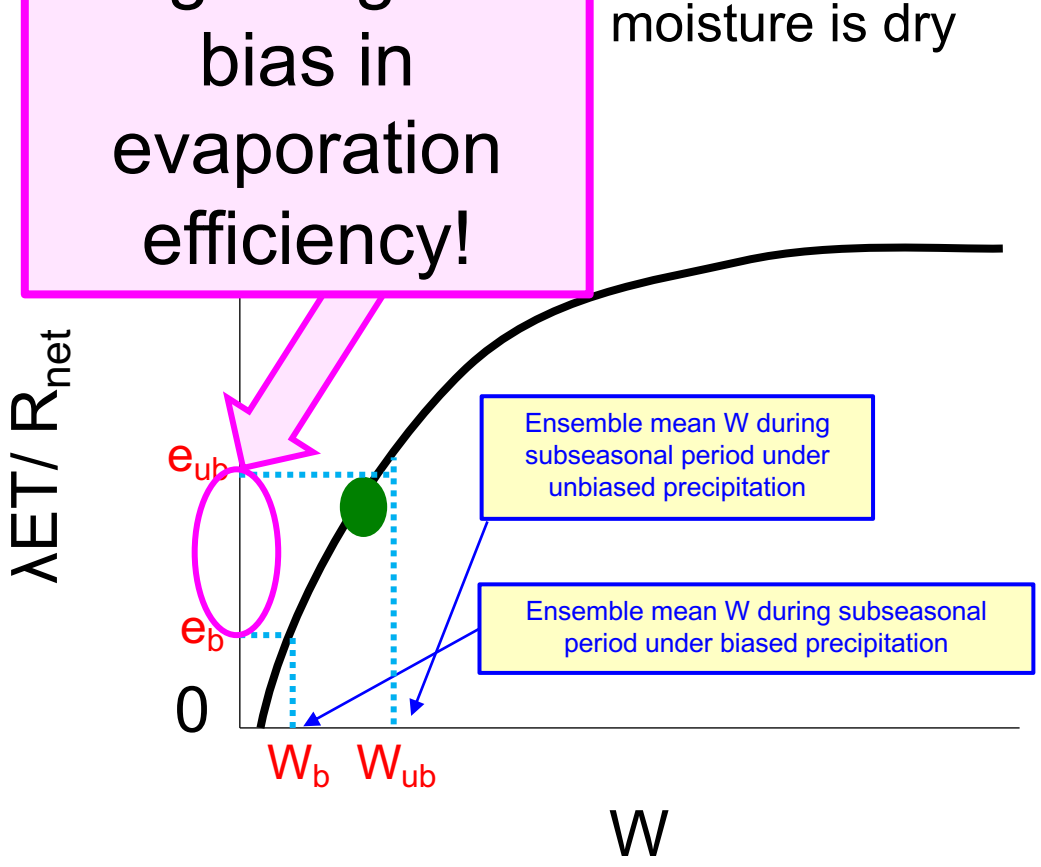


In summary, under a dry precipitation bias,

E bias (dry initialization) > E bias (wet initialization)

which implies

T2M bias (dry initialization) > T2m bias (wet initialization)

Can we see this behavior in forecast model output?

Seasonal forecasting system examined: GMAO's GEOS S2S Version 2.

Forecast focus: Continental US

Years examined: 1999-2015

Start dates: 6 start dates per month (June – August), spaced 5 days apart; 4 ensemble members each

⇨ 102 ensemble-mean forecasts per month

Source of W_0 values: MERRA-2

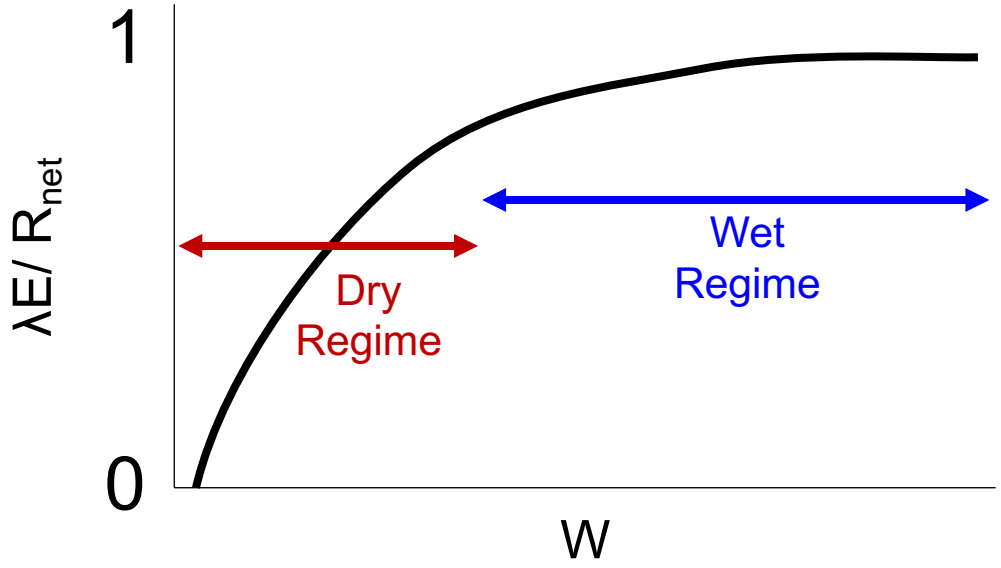
Validation data for T2M: CPC station-based observations

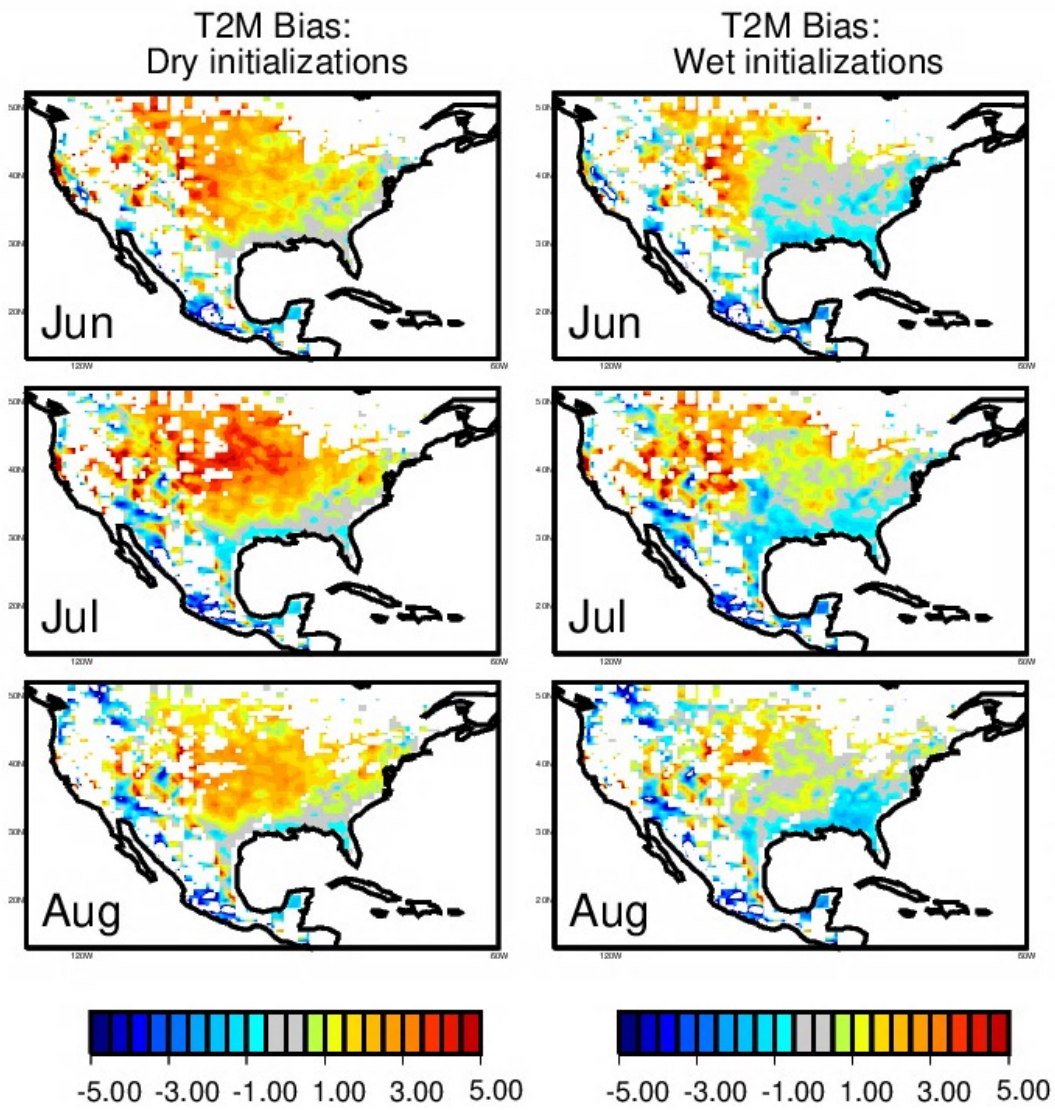
For forecasts initialized in June, July and August, analyze T2M (air temperature) on days 16-30 of the forecast.

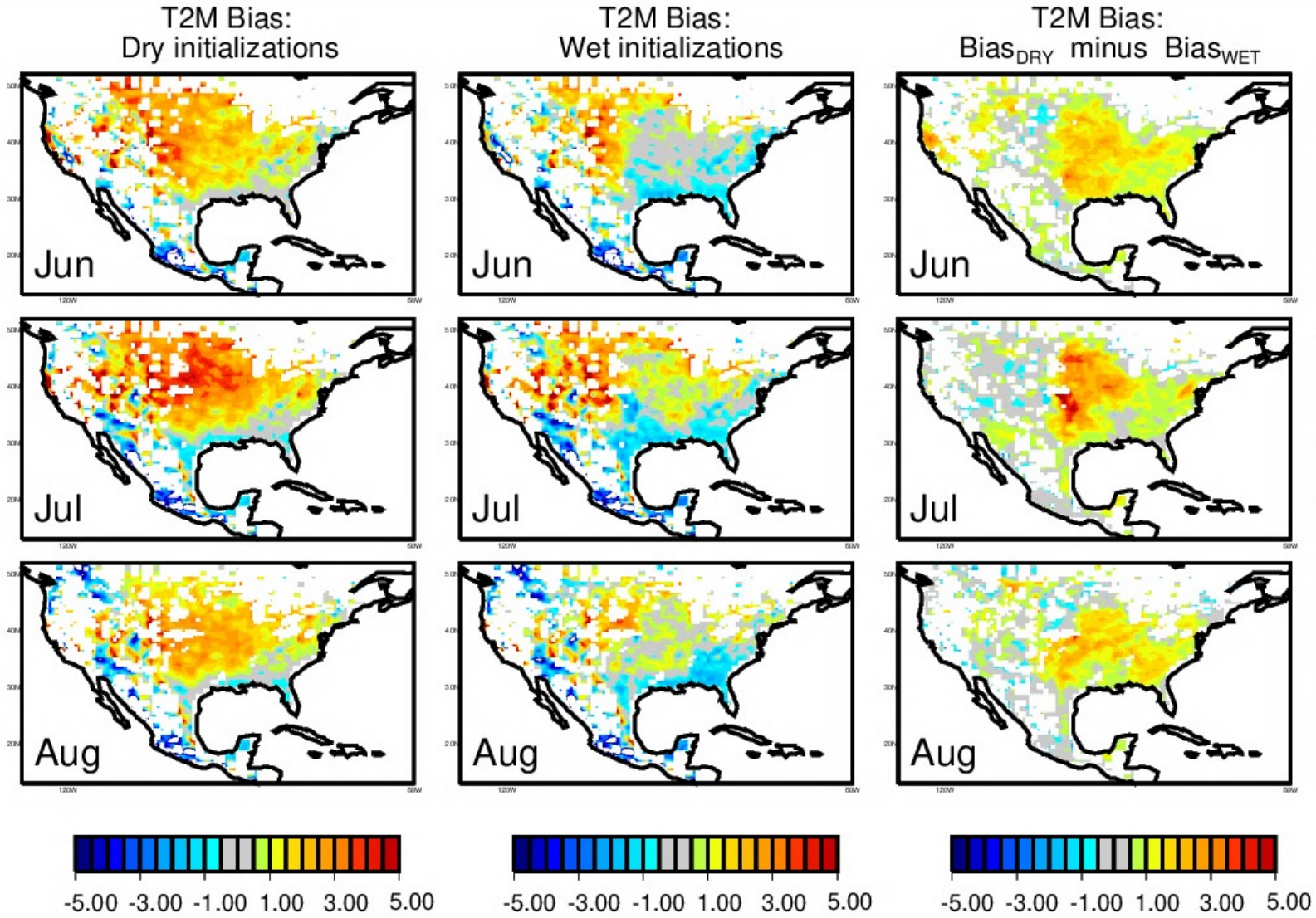
At each grid cell, separate the 102 forecasts into 2 subsets:

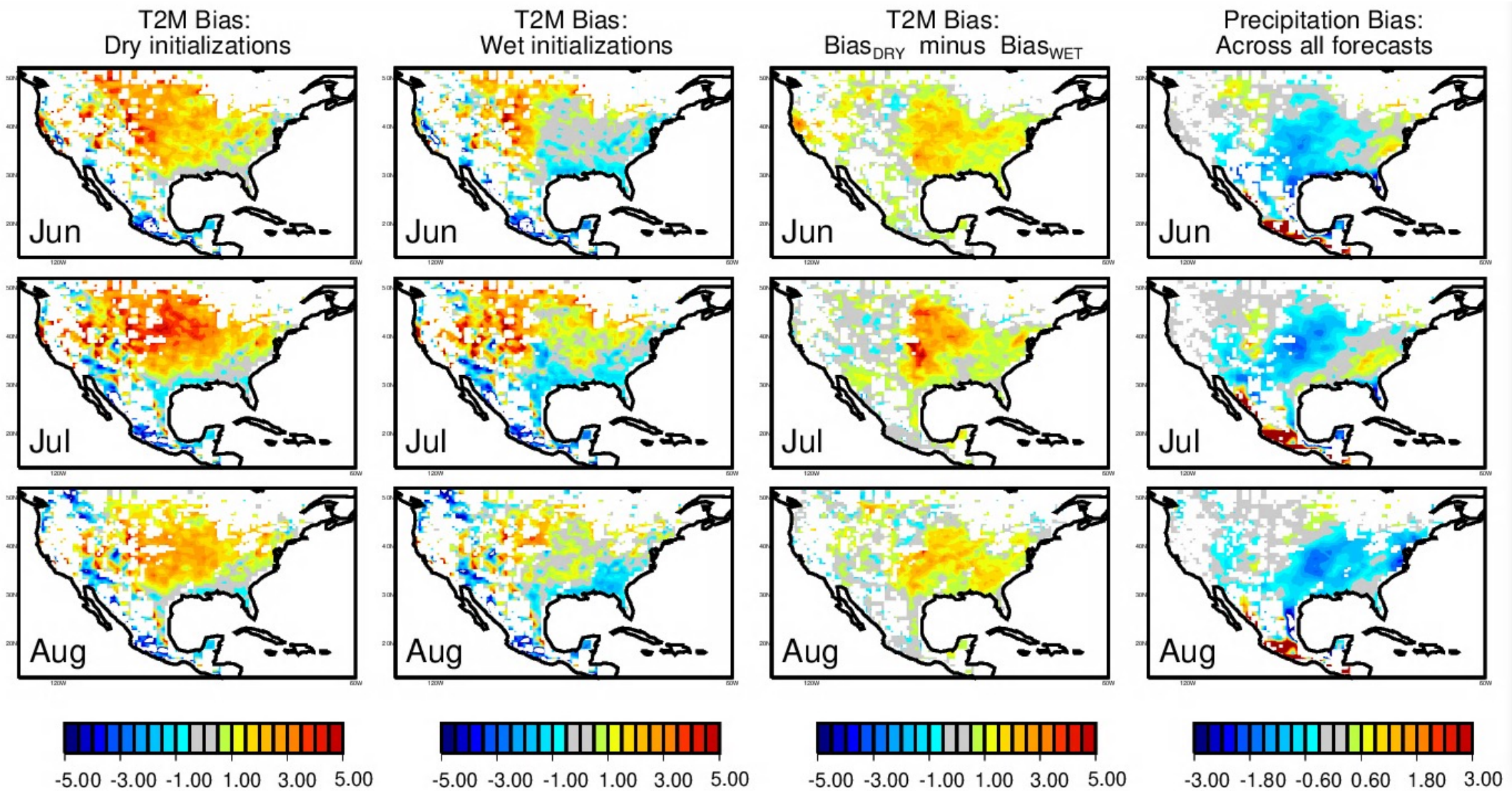
(1) Those with initial soil moisture states in the dry regime

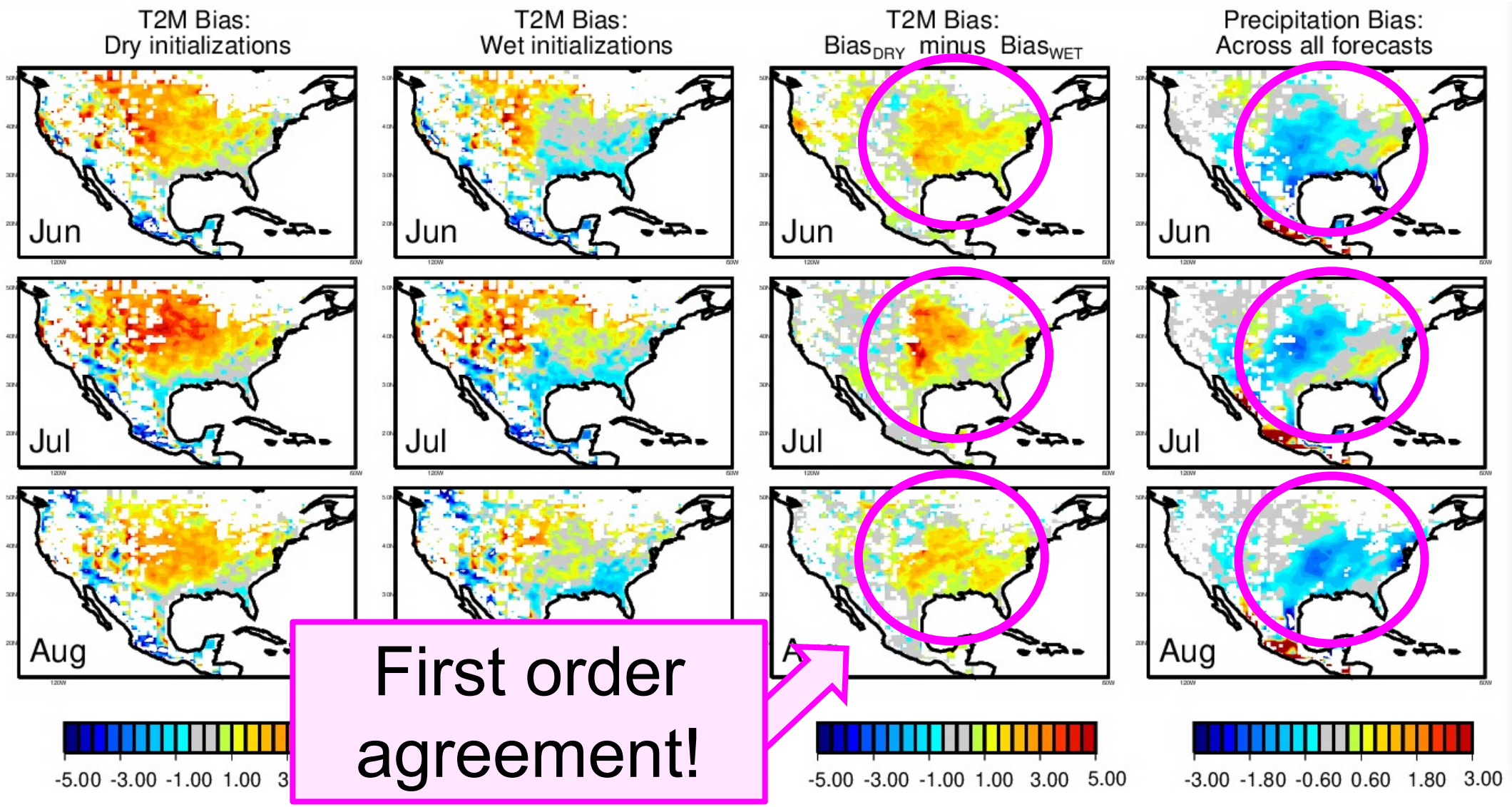
(2) Those with initial soil moisture states in the wet regime




T2M Bias:
Dry initializations
T2M Bias:
Wet initializations
Jun
Jul
Aug
Jun
Jul
Aug
-5.00 -3.00 -1.00 1.00 3.00 5.00
-5.00 -3.00 -1.00 1.00 3.00 5.00


T2M Bias:
Dry initializations
T2M Bias:
Wet initializations
T2M Bias:
Bias$_{DRY}$ minus Bias$_{WET}$
Jun
Jul
Aug
-5.00 -3.00 -1.00 1.00 3.00 5.00


T2M Bias:
Dry initializations
T2M Bias:
Wet initializations
T2M Bias:
Bias$_{DRY}$ minus Bias$_{WET}$
Precipitation Bias:
Across all forecasts
Jun
Jul
Aug
-5.00 -3.00 -1.00 1.00 3.00 5.00
-5.00 -3.00 -1.00 1.00 3.00 5.00
-5.00 -3.00 -1.00 1.00 3.00 5.00
-3.00 -1.80 -0.60 0.60 1.80 3.00

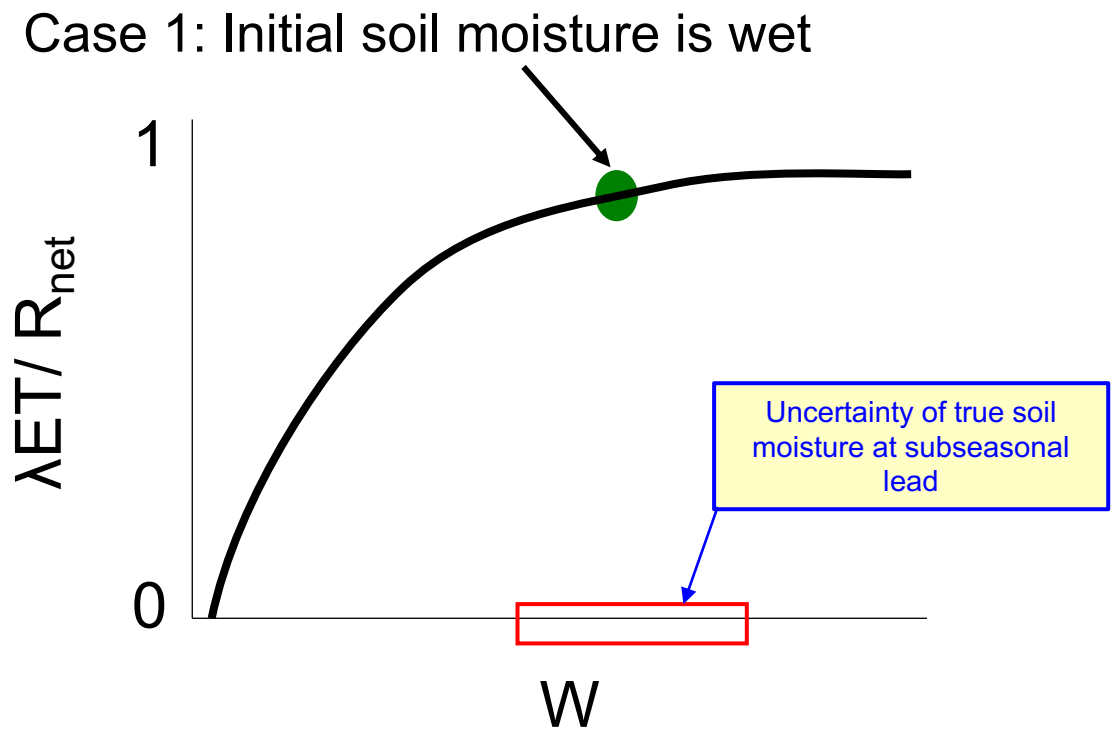


First order agreement!

$$RMSE^2 = bias^2 + ubRMSE^2$$

Mechanism 2: A focus on ubRMSE

Mechanism Affecting ubRMSE



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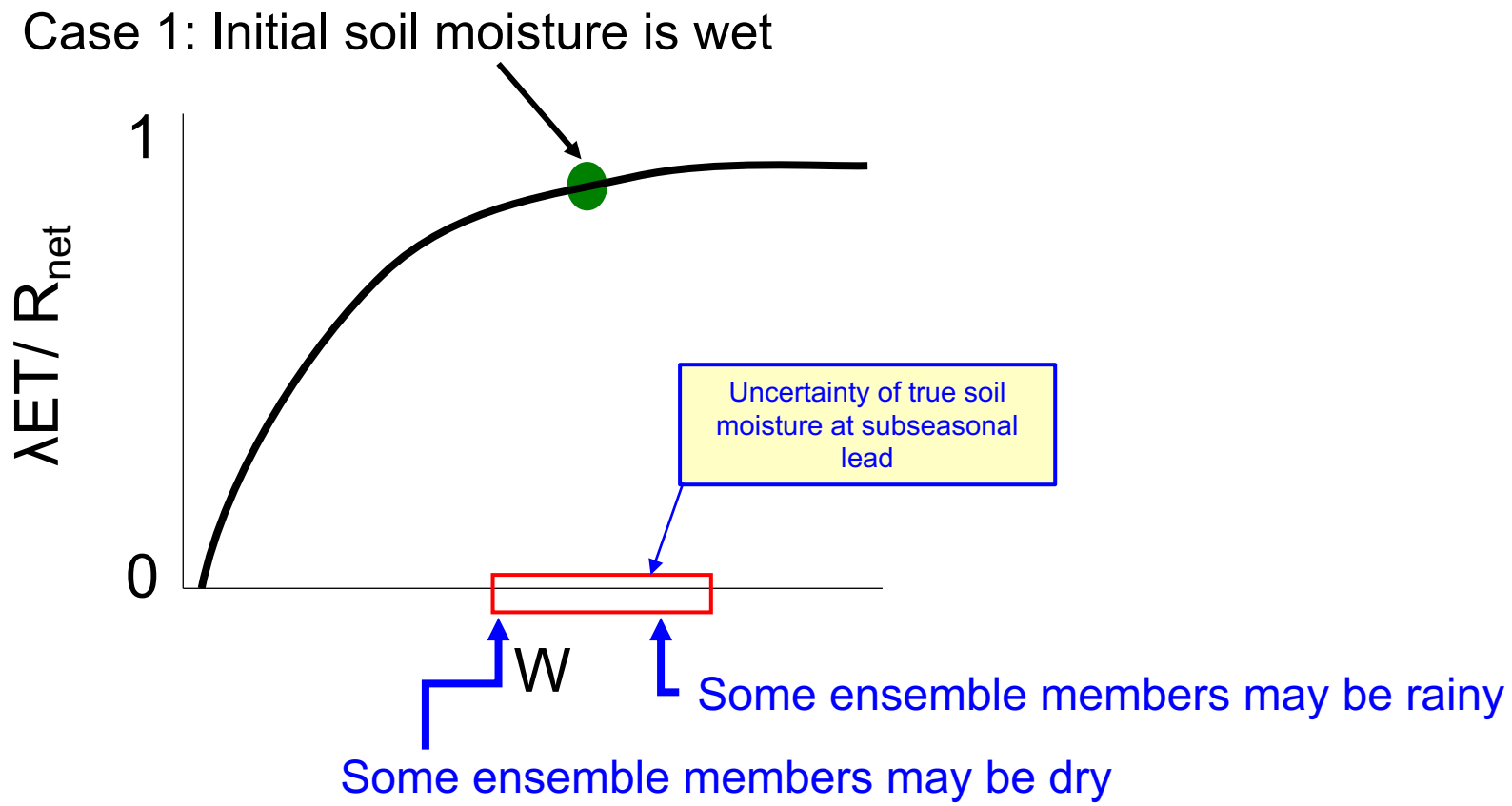

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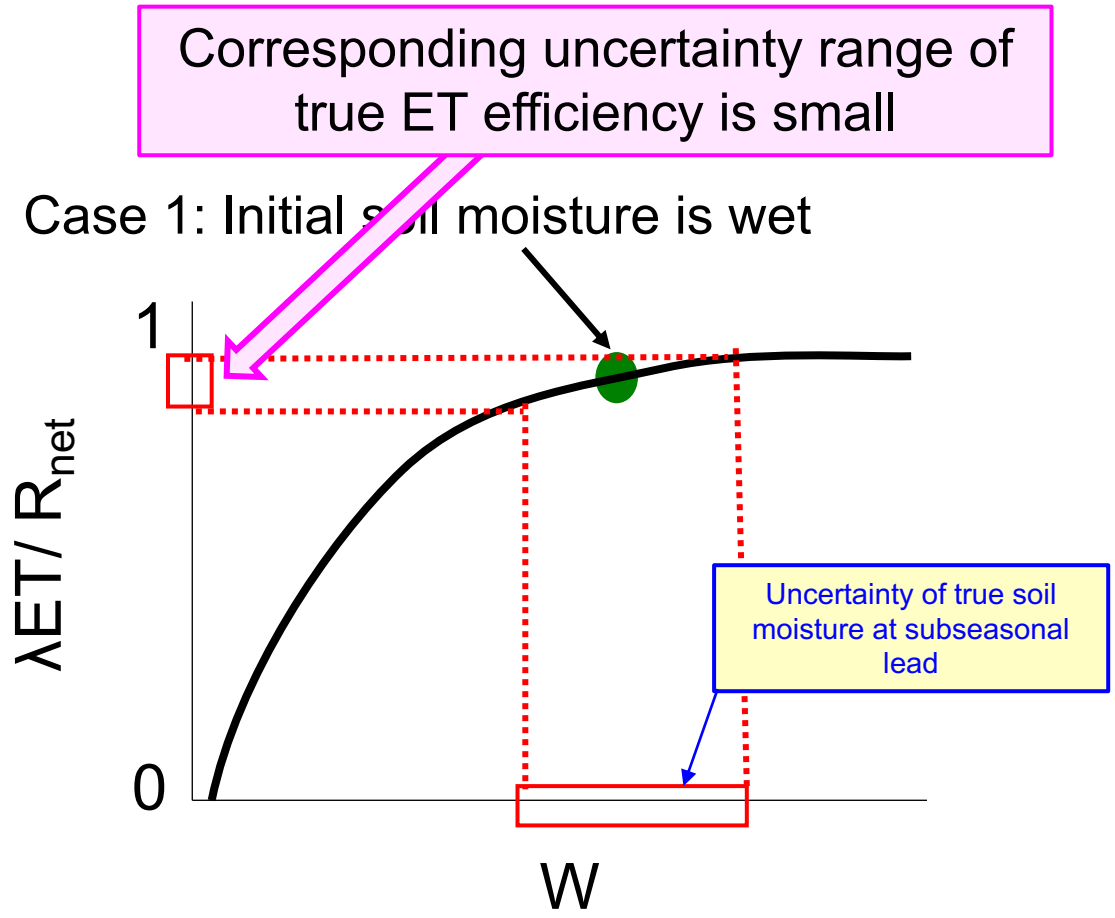

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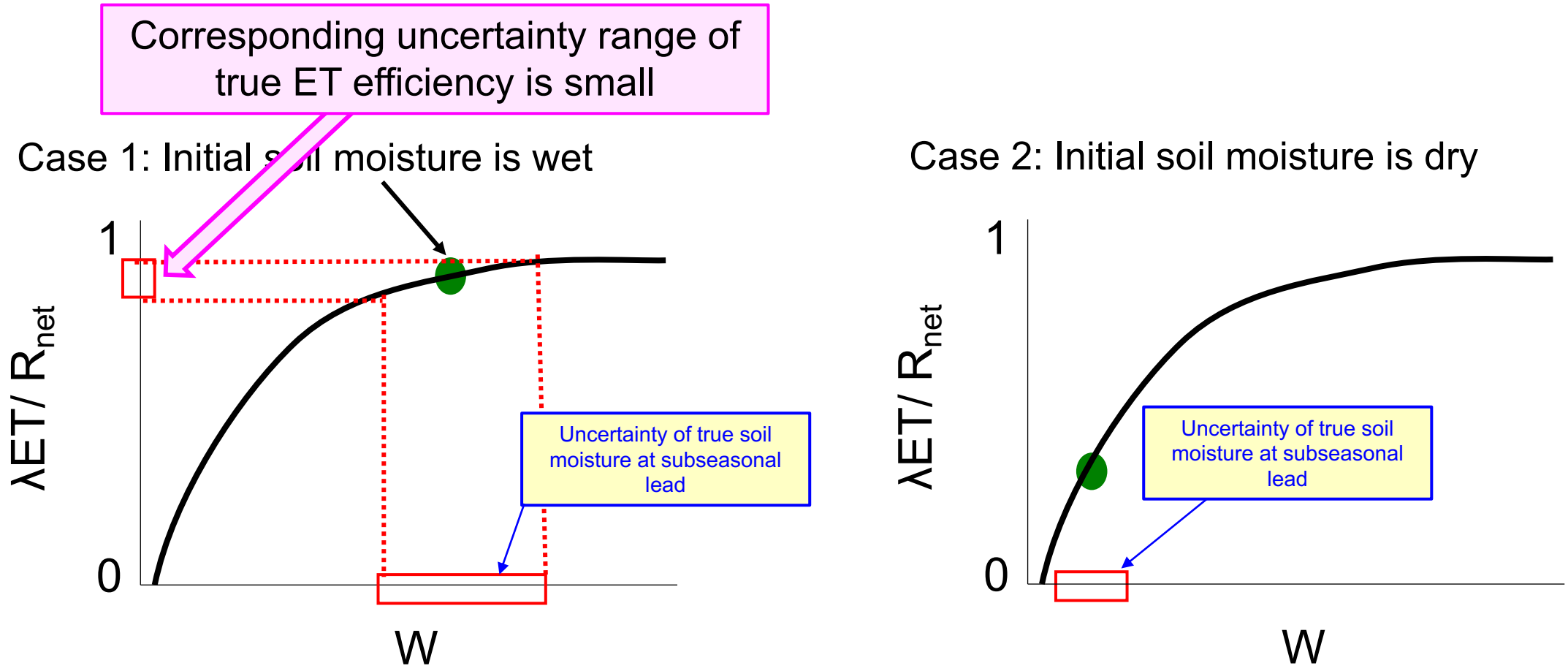
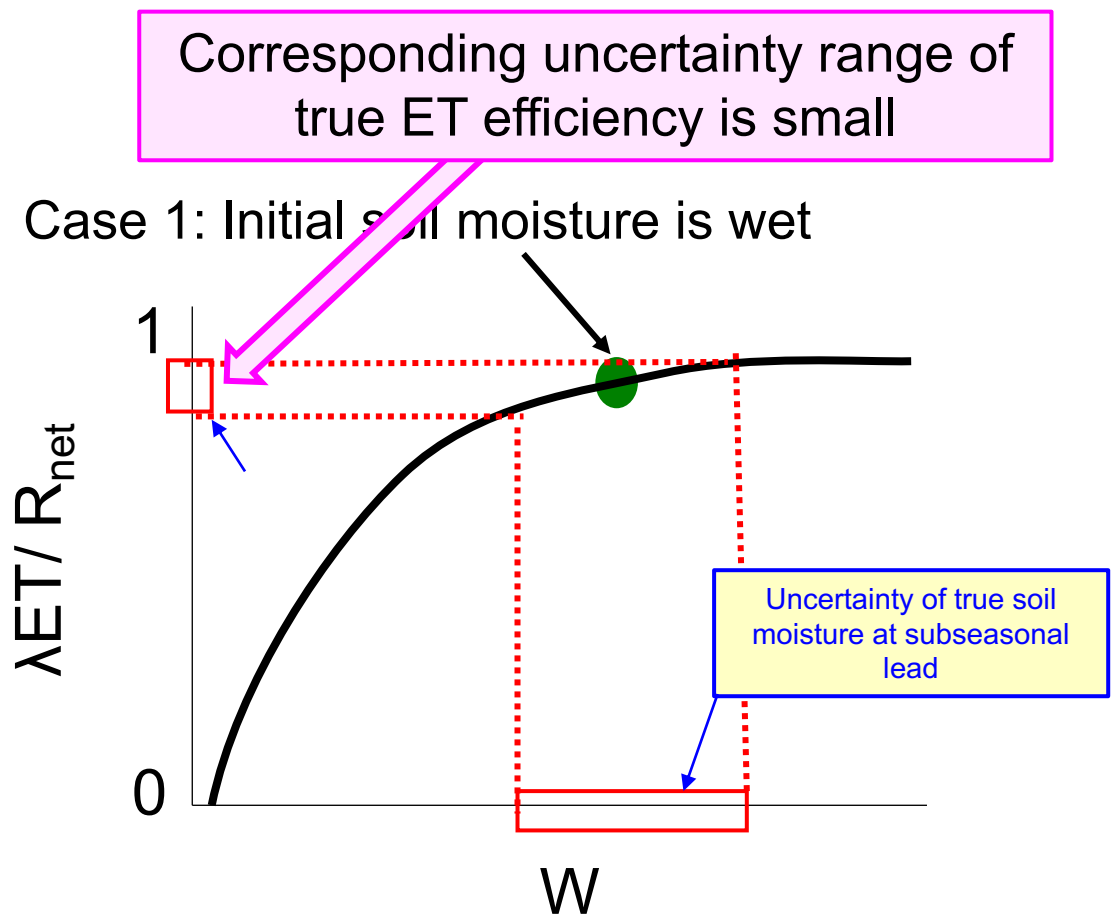
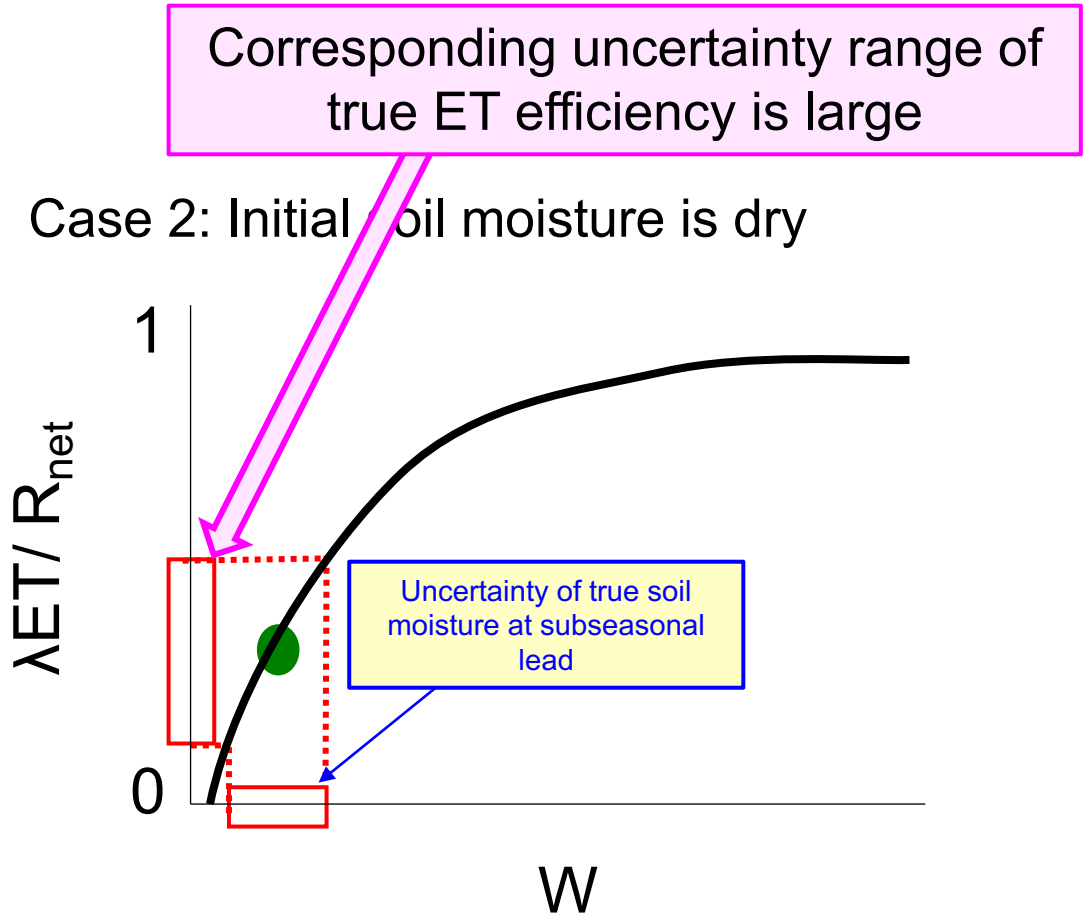


Mechanism Affecting ubRMSE



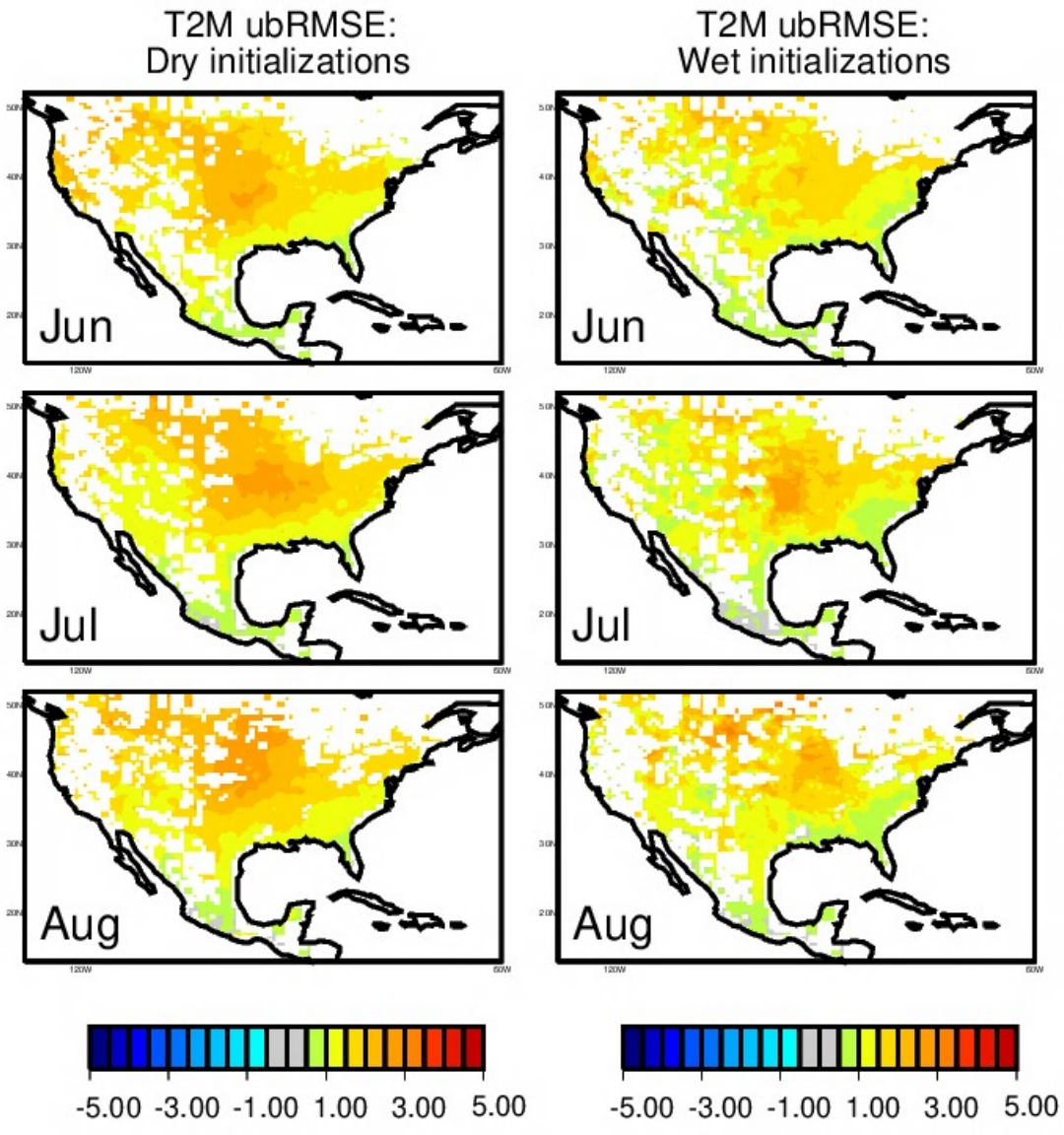


Accordingly,

E uncertainty range (dry initialization)
> E uncertainty range (wet initialization)

which implies

T2M ubRMSE (dry init.) > T2m ubRMSE (wet init.)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Dry initializations
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Jun
Jun
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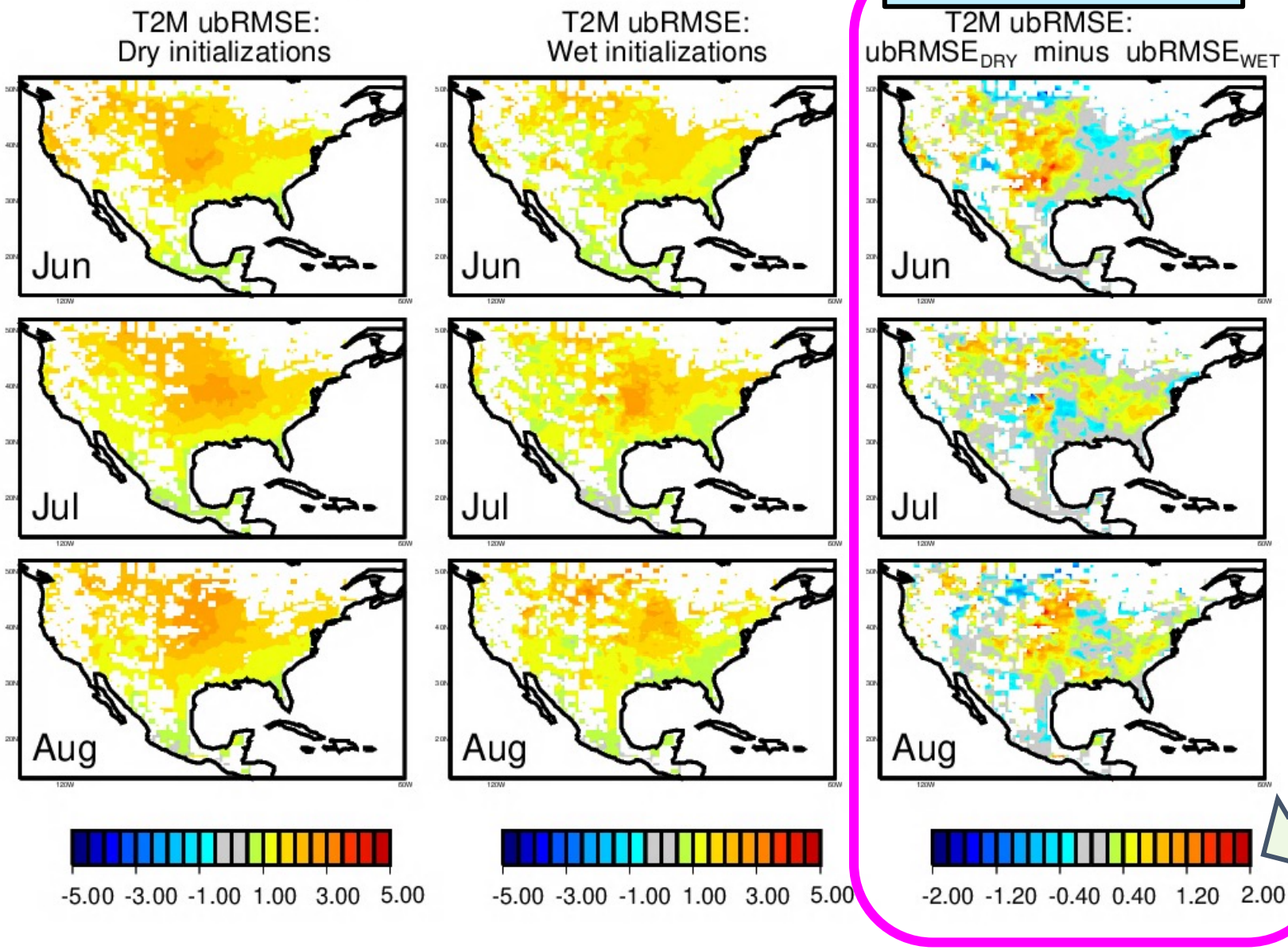
-5.00 -3.00 -1.00 1.00 3.00 5.00
-5.00 -3.00 -1.00 1.00 3.00 5.00

Differences



Values are, as expected, generally positive….

… though the magnitudes of the differences are relatively small (the color bar for the bias analysis went from -5 to 5).

Summary

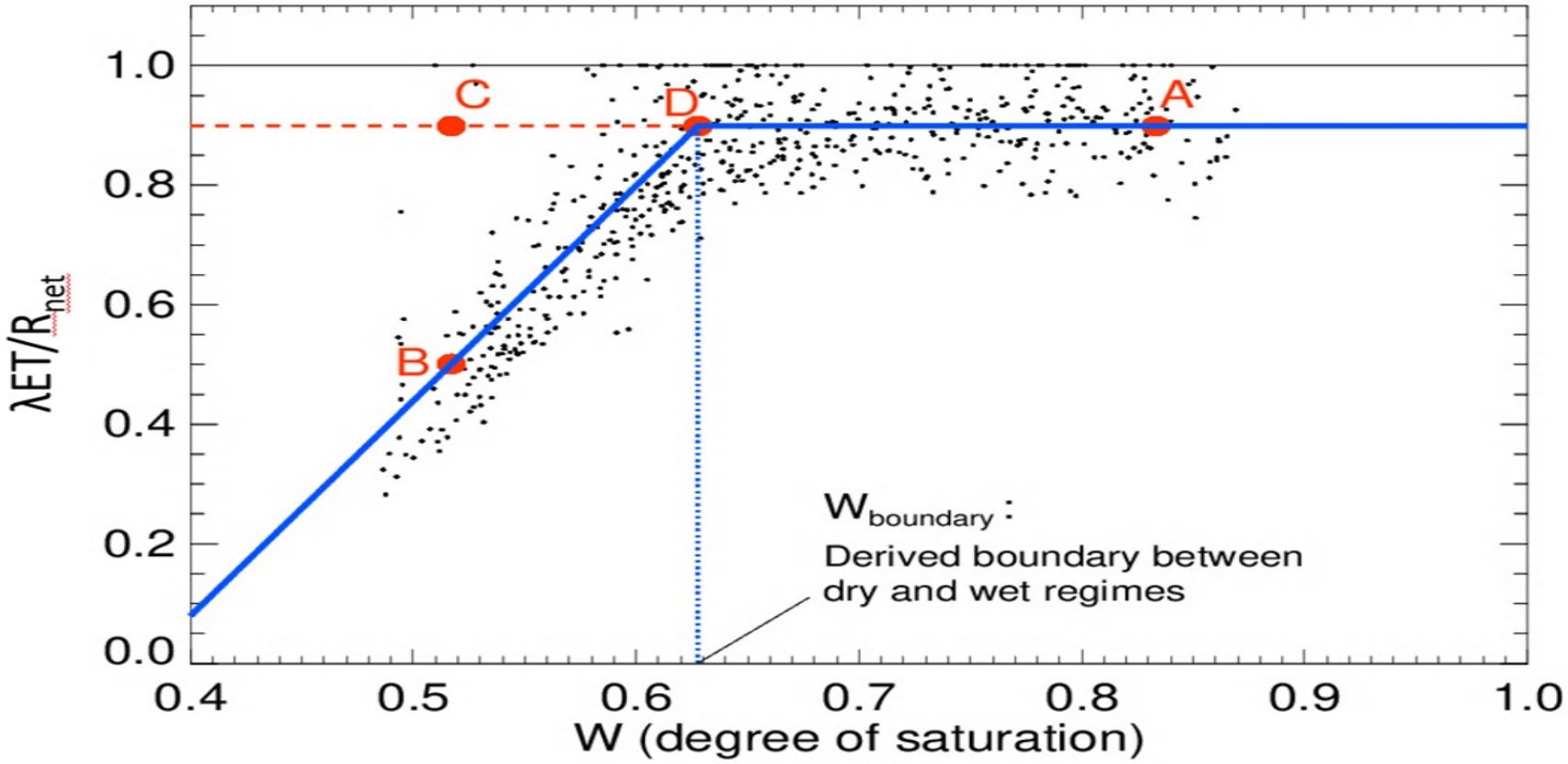
Soil moisture has long been known to influence forecasted air temperature (T2M) at subseasonal leads via land-atmosphere feedback. Here, we:

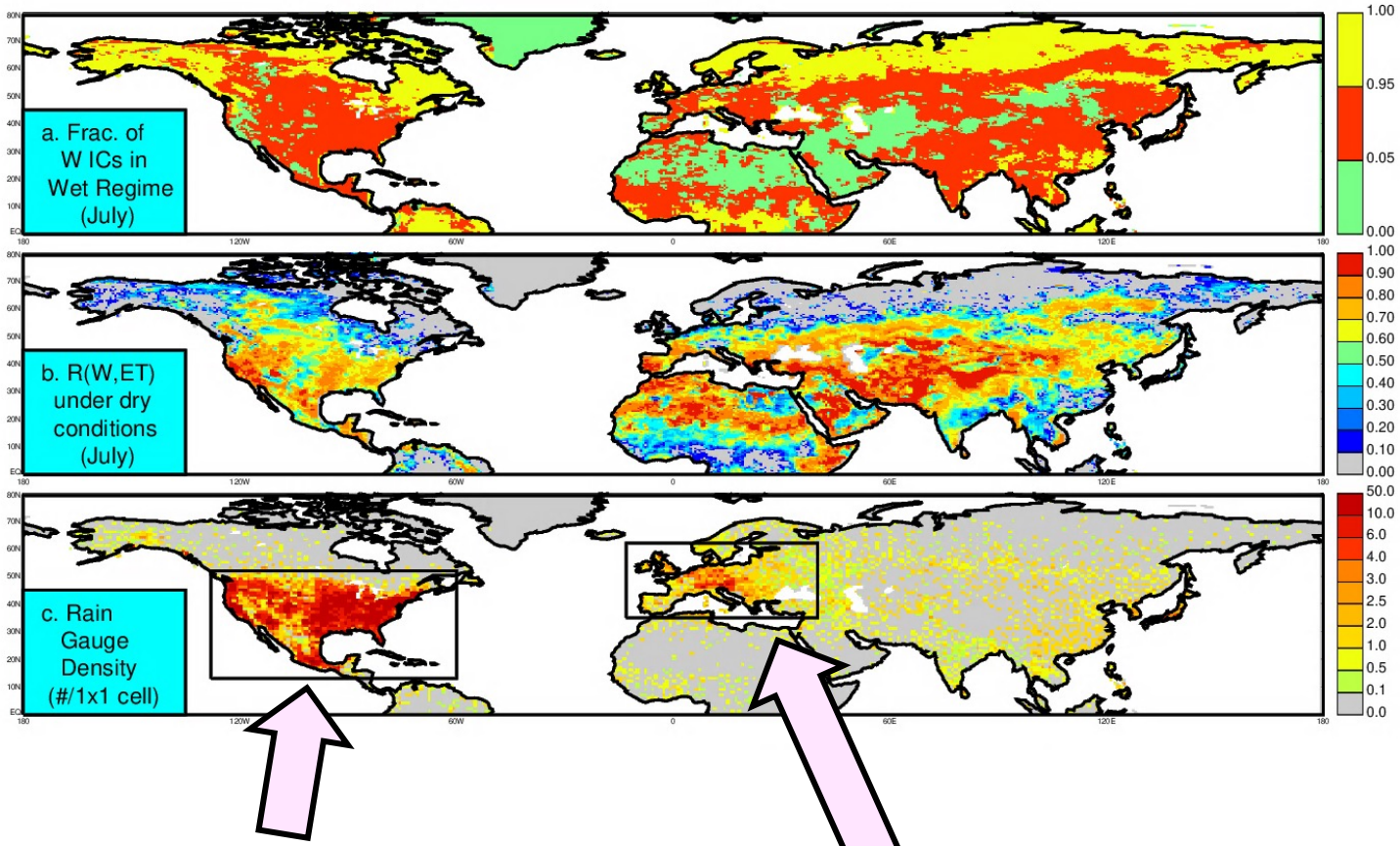
- Illustrate two mechanisms by which a dry soil moisture initialization would affect forecast error differently than would a wet soil moisture initialization.
- Show, using output from a state-of-the-art seasonal forecast system, that in the presence of a precipitation bias, the forecast temperature bias is larger for dry initializations.
- Show, using that output, that the ubRMSE (random error) of forecast T2M tends to be higher for dry initializations.

Thank you!

Extra Slides

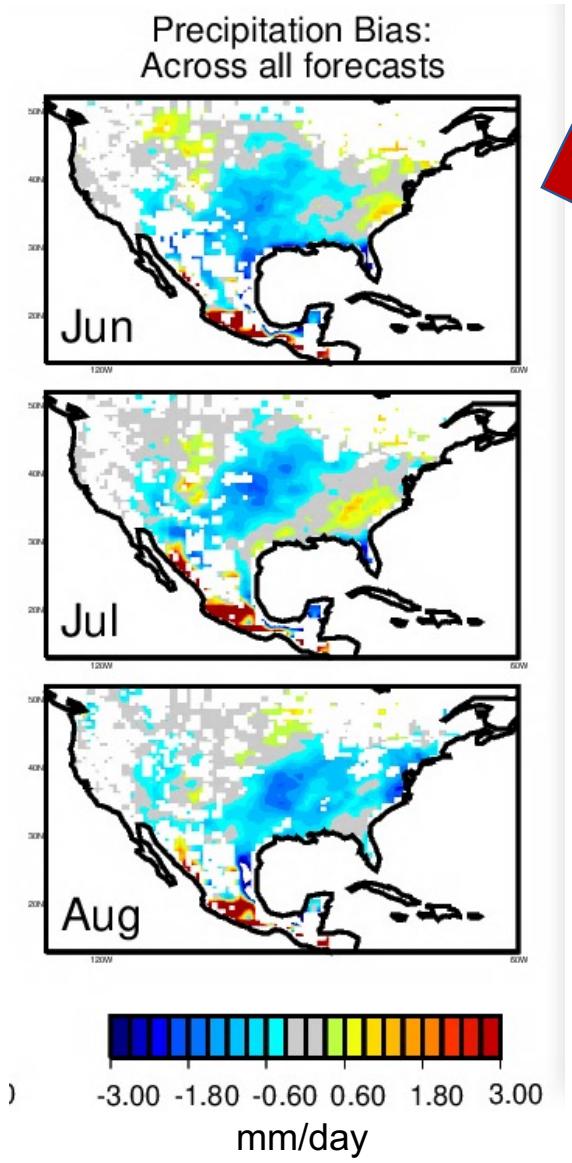
Side note: this separation is actually rather involved. I won't get into it here, but it involves diagnosing the canonical relationship from an independent land model simulation.





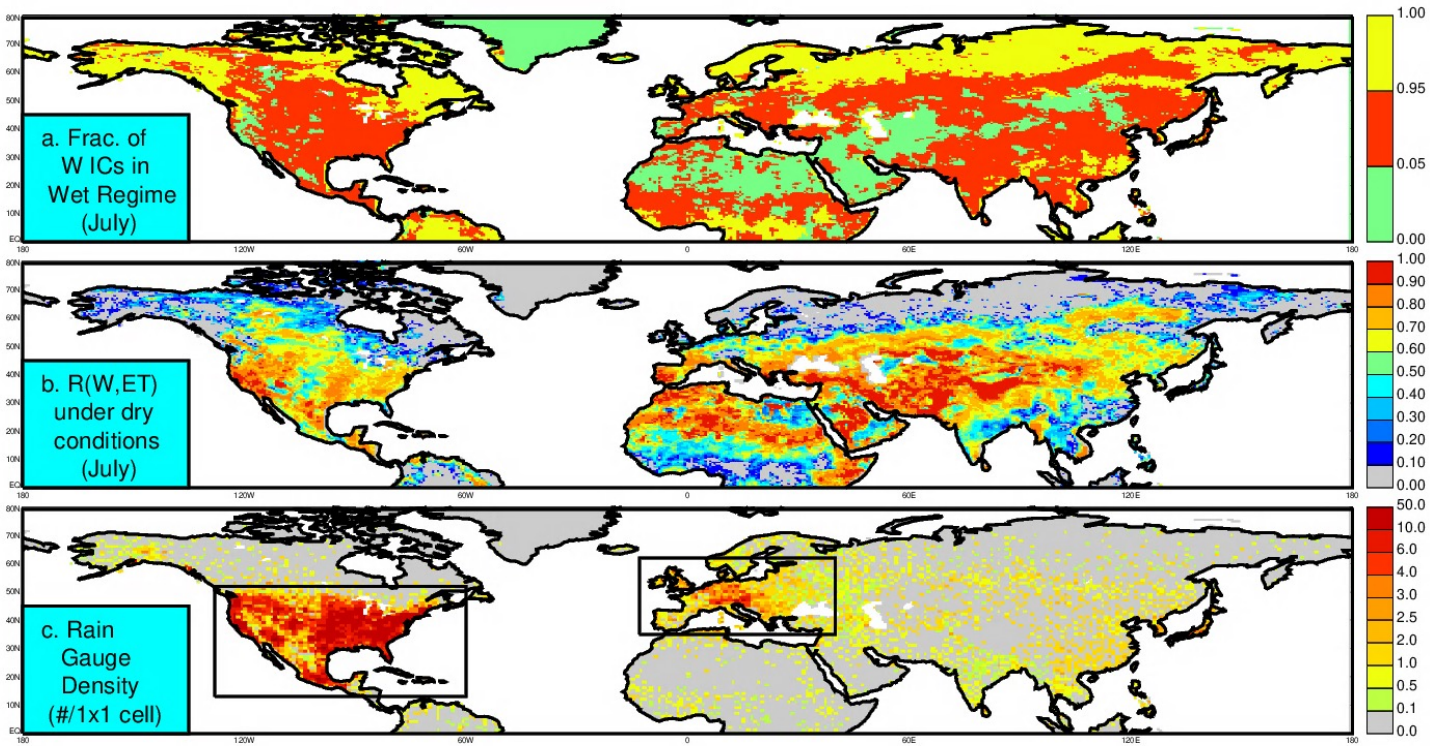
As noted above, the US & Mexico is a valid place to look for these effects, given data availability and other constraints.

We can take a look at Europe too, though there would be some limitations.



We will address this question over the US, a place where most models have a large summertime precipitation deficit…

… and where other critical criteria for a valid evaluation are met



Now compute:

Average T2M bias from forecasts initialized in the dry regime	**minus**	Average T2M bias from forecasts initialized in the wet regime	**= Δ T2M bias**

Is ΔT2M bias > 0 in areas where the average precipitation bias is negative?

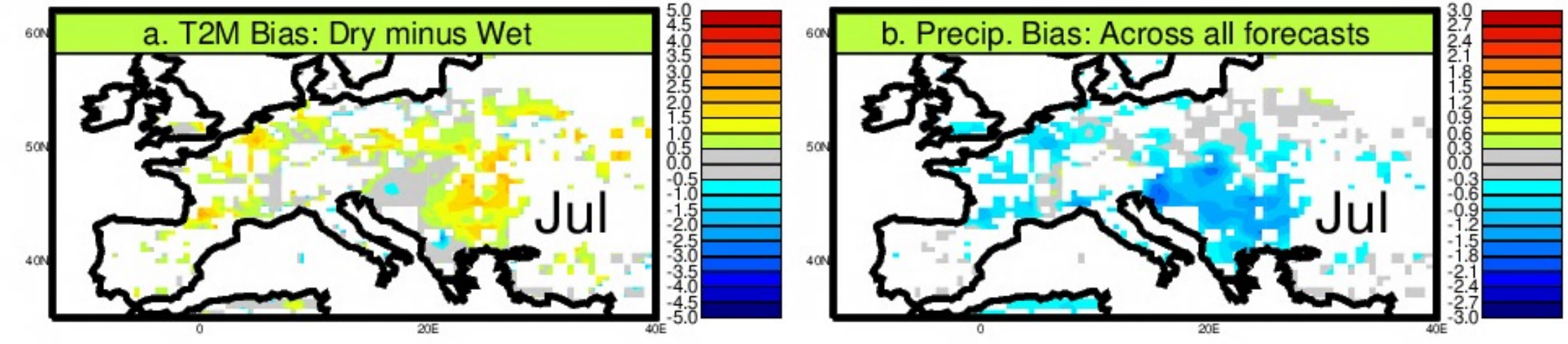
Now look for evidence of this second mechanism in the forecast system output.

Compute

T2M ubRMSE (dry init.) minus T2m ubRMSE (wet init.)

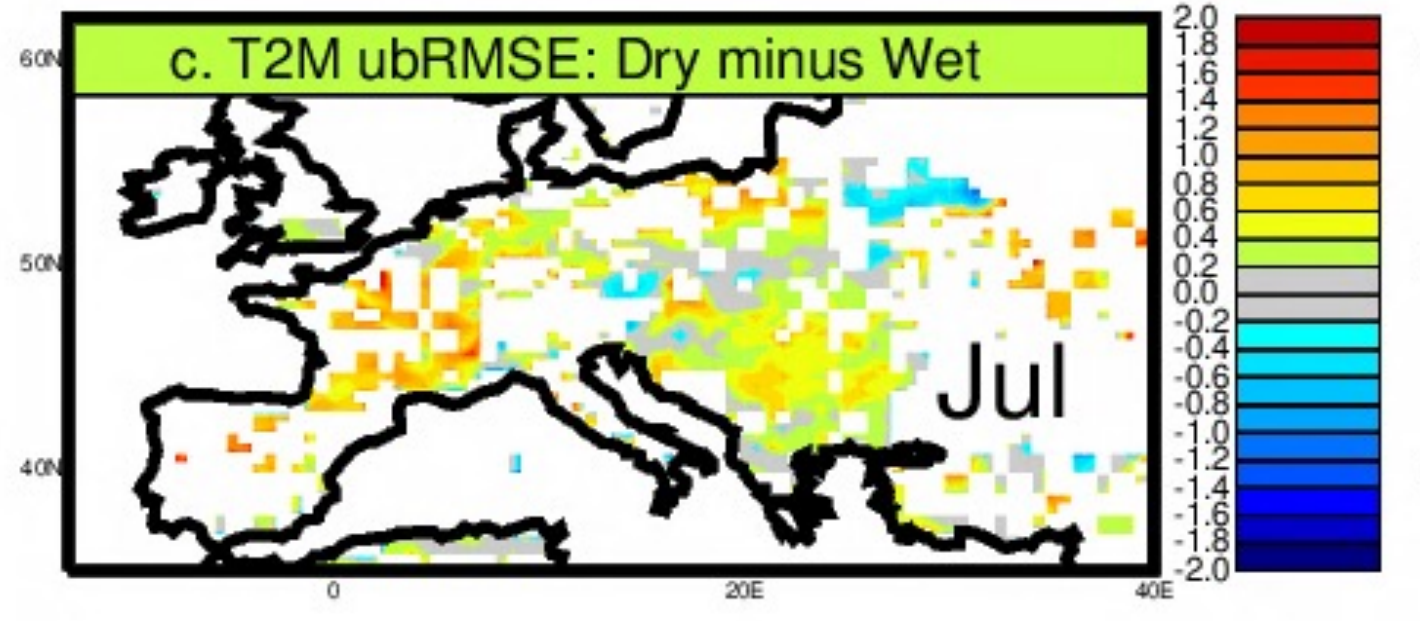
Do we indeed get positive values?

In regions of dry precipitation bias, the forecast system does tend to produce higher T2M forecast biases for dry initializations.



⇨ The bias-focused mechanism appears to be operating!

The T2M forecast ubRMSE also tends to be larger for dry initializations.



⇨ The ubRMSE-focused mechanism appears to be operating! (However, certain additional signatures of the mechanism, not shown here, are not as clear as the are in North America.)